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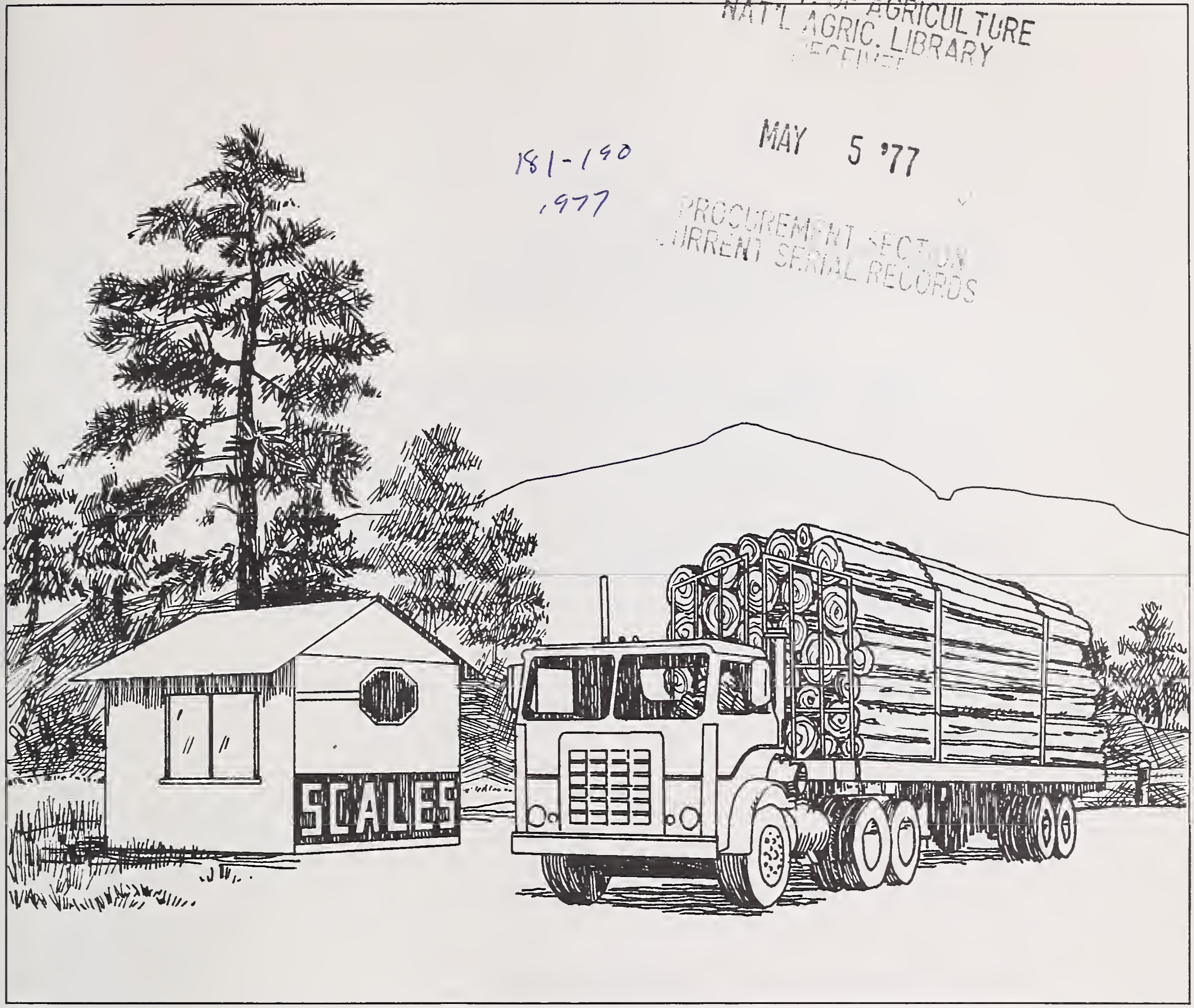

Weight Scaling for Southwestern Ponderosa Pine

Dennis M. Donnelly and Roland L. Barger

January 1977

USDA Forest Service
Research Paper RM-181

Rocky Mountain Forest and
Range Experiment Station
Forest Service
U.S. Department of Agriculture
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Abstract

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Weight scaling is an increasingly important alternative to stick scaling as average saw log size decreases. Regression weight scaling was found to be more precise than sample stick scaling or ratio weight scaling for estimating sale and truckload log volumes, but all three methods were acceptably precise. The most precise regression equation included both net load weight and log count. Individual truckload volumes may be estimated as part of a woodyard inventory system from weight scaling tables generated from regression equations. Potential errors are discussed with examples, and techniques for avoiding these mistakes are suggested.

Keywords: Weight scaling (log), scaling (log), *Pinus ponderosa.*

Acknowledgments

This study was conducted in cooperation with Southwest Forest Industries, and with the Southwest Region and Coconino National Forest, USDA Forest Service. Logs were scaled by personnel of the Coconino National Forest and trucks were weighed on scales at the Southwest Forest Industries sawmill at Flagstaff, Arizona. Data used in this study were collected under the supervision of R. L. Barger, and the final analysis presented here was made by D. M. Donnelly.

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Weight Scaling for Southwestern Ponderosa Pine

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The Study in Brief

Weight scaling, a method of estimating board-foot scale of truckloads of logs widely accepted in other parts of the Nation, can also be used to estimate board-foot scale of ponderosa pine saw logs in the Southwest with generally acceptable levels of precision.

Regression-based weight scaling is more accurate than sample-stick scaling or ratio weight scaling. Among many possible regression equations, three were tested; the most precise of these uses both weight and log count as input information to estimate truckload volume.

Existing computer programs can generate tables for direct determination of truckload volume from weight alone or from weight and number of logs. These weight-scaling tables can be used to estimate total sale volumes and to estimate incoming individual truckloads as part of a woodyard inventory system.

Generalized recommendations are not possible since each weight-scaling opportunity is partially unique. However, several guidelines are worth considering.

Weight scaling must be applied with some discretion. Applying data from one sale or a group of sales may not give accurate results on another sale. If possible, log loads should be grouped according to sale, season, species, size, or other applicable factors. This sorting will eliminate the major sources of weight-scaling variation. Loads can be sampled within each group and separate regressions computed.

An initial sample should be updated by some level of continuous sampling to verify and, if necessary, recompute scaling tables. When we used data from loads scaled in spring to estimate loads weighed in summer and fall, results were inaccurate or marginal for most equations.

A regression involving weight and number of logs enables the user to reduce his sample size while maintaining the precision of ratio weight scaling or sample-stick scaling. Conversely, precision can be increased using a regression when sample size is the same as in ratio weight scaling or sample-stick scaling.

This study did not consider in any detail the economics of weight scaling with respect to costs, value of scaled material, or differences in material size. These relationships for Rocky Mountain timber products may change somewhat with the recent Forest Service commitment to adopt 100 cubic feet of wood (the cunit) as a sale measurement unit. Also, further in the future is the adaptation of scaling methods to the metric system.

Procedural facets of weight scaling such as sampling and statistical analysis are well developed and defined. How these procedures may be applied under future developments in the central and southern Rocky Mountains is open to question. There will undoubtedly be new opportunities to improve on existing methods while these necessary changes are being implemented.

Review of weight-scaling evolution highlighted the areas of investigation in this study: feasibility of weight scaling for southwestern ponderosa pine; sources of variation and error found in weight scaling; and the comparison of performance of regression weight scaling with two traditional methods. In order to use these or any other regression weight-scaling equations, some pitfalls can be avoided and these are discussed.

Background

Saw logs are now weight scaled by the forest products industry in many areas. Acceptance of weight scaling has been increasing as average saw-log size decreases due to depletion of large old-growth timber on easily accessible sites. More logs per thousand feet board measure (M fbm) log scale means more time spent for 100 percent stick scaling.

Sample-stick scaling, ratio weight scaling, and regression weight scaling are among alternatives to stick scaling all logs. Although sample-stick scaling and ratio weight scaling are actually simple forms of regression analysis, a distinction is made between them and the other three regression weight-scaling equations developed in this report.

Sample-stick scaling requires scaling a random sample of log loads for board-foot volume, and multiplying the resulting average volume per load by the number of all incoming loads. For ratio weight scaling, sample loads are both weighed and scaled so that a ratio of mean scale to mean weight can be calculated. This ratio is multiplied by the total weight of all incoming loads to give estimated log scale for all loads. In regression weight scaling—the primary focus of this report—the relationship might

simply be a weight-to-scale ratio. Precision may be improved, however, by an additional variable such as number of logs per truckload.

Weight Scaling—Past and Present

Possibilities for scaling wood products by weight were suggested by Schumacher (1946). In addition to illustrating a volume-weight correlation, he pointed out differences due to sale origin of the logs. Taras (1956) further showed how pulpwood measurement was affected by log diameter, length, and moisture content. The close correlation between saw-log board-foot volume and weight was demonstrated by Guttenberg et al. (1960).

Early workers did not deal with the effect of saw-log size, either directly or in terms of logs per load. A later study showed that using number of logs per truckload increased scaling accuracy for logs of mixed lengths (Bair 1965). For a given log-load weight, board-foot scale decreases as log number increases, so using number of logs per truckload as a scaling variable accounts indirectly for log size.

Computerized printing of scaling tables based on weight and number of logs per truckload was demonstrated by Row and Fasick (1966). Weldon (1967) showed it was feasible to weight scale truckloads of mixed pine and hardwood logs. More recently, weight scaling has been extended to include truckloads of tree-length logs for multiproduct conversion (Guttenberg and Fasick 1973, Tyre et al. 1973, Fasick et al. 1974). This application can be useful in log concentration and sorting yards where long logs are bucked for various uses—saw logs, veneer logs, or pulpwood—to improve utilization and economic return.

Study Objectives

This study had three objectives:

1. To test the feasibility of regression weight scaling as a means of scaling both truckloads of southwestern ponderosa pine saw logs and total log output from a sale over a period of time.
2. To identify and evaluate potential sources of variation that may reduce reliability of weight scaling for southwestern ponderosa pine.
3. To compare the relative precision of regression weight scaling against sample-stick scaling and ratio weight scaling.

Scaling research with other species has demonstrated that gross board-foot volume is correlated with weight and number of logs per load. This relationship may be complicated by other factors acting singly or in combination; for example, species mix, heartwood-sapwood proportion, specific gravity, moisture content, bark, defect, and log size. Although only easily measured variables can be economically used to estimate gross scale, weight-scale users should know the effects of these other factors. Consequently, variables of season, log mix, and sale area were evaluated as part of this study.

How the Study Was Conducted

Ponderosa pine weight-scale data were collected at a sawmill near Flagstaff, Arizona. Data were collected on two randomly picked days each week from April through December. The first truck arriving after 8 a.m. was designated the initial observation, and every following fifth load was sampled. Mixed species loads were not sampled. A total of 539 truckloads of logs from nine sales were measured (table 1).

For each truckload, the following data were tallied:

Data taken at truck scales:
- Date.
- Load number.
- Logging unit (sale) origin.
- Gross, tare, and net truck weights.

Data taken in the log yard:
- Total number of pieces in the load.
- Number of "blackjack" (young growth) pieces in the load.

Data taken on the sawmill deck:
- Gross scale (Scribner Decimal C log rule for all scale measurements).
- Defect scale.
- Net scale.
- Total number of standard 16-foot saw logs scaled.

We used several statistical methods to analyze the data. First, three regression equations incorporating load weight and number of logs were used to estimate gross board-foot volume per truckload for all sales together. Since it is probable that other log qualities influenced estimation accuracy, an analysis of variance next helped identify these factors. We considered season, load mix of blackjack and yellow pine, log length, and sale origin. Finally, we compared the predictions of several scaling equations—sample-stick scaling, ratio weight scaling, and the best of the three regression weight scaling equations. For these comparisons we chose 4 percent error as a limit of scaling accuracy. Thus in the following discussions, equations and weight-scaling methods that estimated gross scale within 4 percent of the known value were considered adequate.

Table 1.--Data summary (by sale) of saw-log volume, weight, and number of logs per truckload

Sale name	Truck-loads	Saw-log volume			Weight			Logs		
		Average load	Standard deviation	Range	Average load	Standard deviation	Range	Average load	Standard deviation	Range
	No.	- - - - *M fbm* - - - -			- - - - *Pounds* - - - -			- - - - *No.* - - - -		
Bly	228	5.354	0.777	7.380 - 3.110	47,181	5,276	62,910 - 33,550	12.6	2.6	23 - 7
Fisher	22	5.326	.621	6.100 - 3.740	59,958	12,843	98,020 - 43,680	15.1	2.1	22 - 12
Munds	6	4.915	1.010	6.150 - 3.060	51,127	6,826	58,280 - 38,660	18.2	4.4	26 - 14
Newman	104	5.288	.721	7.070 - 3.600	54,312	5,987	65,060 - 27,750	17.9	3.7	28 - 10
Pine Mountain	116	4.272	.800	7.250 - 2.480	44,491	6,509	79,770 - 35,260	16.8	6.0	36 - 8
Robber's Roost	29	5.286	.939	7.840 - 3.490	50,234	5,540	63,050 - 40,330	16.4	3.2	25 - 11
Thomas	1	4.940	--	-- --	59,800	--	-- --	18.0	--	-- --
Watershed	1	2.940	--	-- --	44,180	--	-- --	22.0	--	-- --
Whitehorse Burn	32	4.282	1.135	6.540 - 1.600	56,766	9,801	75,490 - 28,540	29.8	10.2	69 - 16
Total or weighted average value	[1]539	5.030	.930	7.840 - 1.600	49,295	7,721	98,020 - 27,750	15.9	6.1	69 - 7

[1]This figure is total number of truckloads sampled. All other figures in the row, except range values, are weighted averages for all data.

Results of the Study

Regression Weight Scaling

Three different regression equations were used to estimate truckload board-foot volume. All used weight as an input factor; two equations also used number of logs per load:

$$\hat{v} = b_0 + b_1 w \quad \text{[Eq. 1]}$$
$$\hat{v} = b_0 + b_1 w + b_2 n \quad \text{[Eq. 2]}$$
$$\hat{v} = b_0 + b_1 w + b_2 n + b_3 \sqrt{w\,n} \quad \text{[Eq. 3]}$$

where:

$\hat{v}$ = estimated truckload gross saw-log volume in thousands of board feet,

w = truckload net log weight in thousands of pounds,

n = number of logs on the truckload,

b_0, b_1, b_2, and b_3 = regression coefficients.

Table 2 summarizes regression equations obtained by fitting the three equations to all weight-scaling data and to two data subsets.

In table 2, the R^2 statistic indicates the amount of statistical variation explained by each regression. For example, regression equation 1, applied to all data, explains 29 percent of total variation in the dependent variable, that is, volume per truckload. Standard error of the estimate (SE est.) is a measure of how precisely the regression equation predicts volume. (The smaller the standard error the better.) It can also be used with other quantities to compute a statistical confidence interval around a predicted value. With respect to table 2, note that standard errors of an estimate can be compared only within a sample data group, not between data groups.

Low values for R^2 were a surprising initial result. In studies cited earlier, correlation between board-foot scale and weight yielded R^2 values of 0.80 or better for southern pine saw logs. Since the Doyle and International log rules predominate in the South, it is possible—though unlikely—that scaling by Scribner Decimal C might be different. We did not have data to test this difference. Row and Guttenberg (1966) obtained R^2 of 0.89 or better with the International Rule and Eq. 3, however.

Table 2.--Summary of regression coefficients (b_0, b_1, b_2, b_3), their standard errors,[1] and the coefficients of variation (R^2)[2] for three equations applied to three data groups; the dependent variable is truckload volume in thousand board feet (M fbm)

Data group and regression equation number	(b_0)	Truckload weight, w (b_1)	Logs on truckload, n (b_2)	$\sqrt{w\,n}$ (b_3)	R^2	S.E. estimate
ALL DATA (539 loads):						
1	1.83620	0.06479 (0.00438)			0.29	0.7851
2	2.46619	0.07935 (0.00344)	-0.08467 (0.00436)		.58	.6018
3	2.57804	0.12843 (0.01139)	0.04492 (0.02904)	-0.16641 (0.03688)	.60	.5910
DATA FOR BLY SALE ONLY:						
1	-0.20734	0.11787 (0.00587)			.64	.4670
2	0.90655	0.11792 (0.00511)	-0.08875 (0.01030)		.73	.4059
3	0.87577	0.10038 (0.02891)	-0.15355 (0.10562)	0.06916 (0.11218)	.73	.4064
DATA FOR SPRING SEASON ONLY:						
1	2.08108	0.06065 (0.00586)			.33	.7002
2	2.73903	0.07573 (0.00538)	-0.09395 (0.01102)		.50	.6064
3	2.67032	-0.01374 (0.03810)	-0.38654 (0.12385)	0.32883 (0.13866)	.51	.5999

[1]Standard errors appear below their respective coefficients within parentheses.
[2]Although R^2 in the table is a decimal proportion, it is also common to speak of "percent variation explained." Thus, 0.29 means "29% of the variation explained by the regression."

Computer analysis of our data by means of Eq. 3 yielded a set of weight-scaling tables (fig. 1; these tables are examples for a specific situation only, and should not be used for any ongoing application). Output from the computer analysis included regression coefficients for the specific equation (see table

8 LOGS

POUNDS THOUSANDS	HUNDREDS 000	200	400	600	800
	M BOARD FEET				
45000	5.559(2.09)	5.578(2.10)	5.597(2.10)	5.615(2.12)	5.634(2.13)
46000	5.653(2.14)	5.672(2.15)	5.690(2.16)	5.709(2.17)	5.728(2.18)
47000	5.747(2.20)	5.766(2.21)	5.784(2.22)	5.803(2.23)	5.822(2.25)
48000	5.841(2.26)	5.860(2.27)	5.879(2.29)	5.898(2.30)	5.917(2.32)
49000	5.936(2.33)	5.955(2.35)	5.974(2.36)	5.993(2.38)	6.012(2.39)
50000	6.031(2.41)	6.050(2.42)	6.069(2.44)	6.088(2.46)	6.107(2.47)
51000	6.126(2.49)	6.145(2.51)	6.164(2.52)	6.183(2.54)	6.202(2.55)
52000	6.222(2.57)	6.241(2.59)	6.260(2.61)	6.279(2.62)	6.298(2.64)
53000	6.318(2.66)	6.337(2.67)	6.356(2.69)	6.375(2.71)	6.395(2.73)
54000	6.414(2.74)	6.433(2.76)	6.452(2.78)	6.472(2.80)	6.491(2.82)

16 LOGS

POUNDS THOUSANDS	HUNDREDS 000	200	400	600	800
	M BOARD FEET				
45000	4.611(1.41)	4.627(1.39)	4.642(1.38)	4.658(1.36)	4.674(1.35)
46000	4.690(1.34)	4.706(1.32)	4.722(1.31)	4.738(1.30)	4.754(1.28)
47000	4.770(1.27)	4.786(1.26)	4.802(1.25)	4.818(1.24)	4.834(1.23)
48000	4.850(1.22)	4.866(1.21)	4.882(1.21)	4.898(1.20)	4.914(1.19)
49000	4.930(1.18)	4.947(1.18)	4.963(1.17)	4.979(1.17)	4.995(1.16)
50000	5.011(1.16)	5.028(1.16)	5.044(1.15)	5.060(1.15)	5.077(1.15)
51000	5.093(1.15)	5.109(1.15)	5.126(1.14)	5.142(1.14)	5.159(1.14)
52000	5.175(1.15)	5.192(1.15)	5.208(1.15)	5.225(1.15)	5.241(1.15)
53000	5.258(1.16)	5.274(1.16)	5.291(1.16)	5.307(1.17)	5.324(1.17)
54000	5.341(1.18)	5.357(1.18)	5.374(1.19)	5.391(1.19)	5.407(1.20)

32 LOGS

POUNDS THOUSANDS	HUNDREDS 000	200	400	600	800
	M BOARD FEET				
45000	3.480(4.79)	3.492(4.74)	3.503(4.69)	3.515(4.64)	3.527(4.58)
46000	3.539(4.53)	3.550(4.49)	3.562(4.44)	3.574(4.39)	3.586(4.34)
47000	3.598(4.30)	3.610(4.26)	3.622(4.21)	3.634(4.17)	3.646(4.13)
48000	3.658(4.09)	3.670(4.05)	3.682(4.01)	3.695(3.97)	3.707(3.94)
49000	3.719(3.90)	3.731(3.87)	3.744(3.83)	3.756(3.80)	3.768(3.77)
50000	3.781(3.74)	3.793(3.71)	3.805(3.68)	3.818(3.65)	3.830(3.62)
51000	3.843(3.59)	3.855(3.57)	3.868(3.54)	3.880(3.52)	3.893(3.49)
52000	3.906(3.47)	3.918(3.45)	3.931(3.43)	3.944(3.40)	3.956(3.38)
53000	3.969(3.37)	3.982(3.35)	3.995(3.33)	4.007(3.31)	4.020(3.30)
54000	4.033(3.28)	4.046(3.27)	4.059(3.25)	4.072(3.24)	4.085(3.22)

60 LOGS

POUNDS THOUSANDS	HUNDREDS 000	200	400	600	800
	M BOARD FEET				
45000	2.406(30.48)	2.412(30.24)	2.419(30.00)	2.425(29.77)	2.432(29.53)
46000	2.439(29.30)	2.445(29.07)	2.452(28.84)	2.459(28.61)	2.466(28.39)
47000	2.472(28.16)	2.479(27.94)	2.486(27.72)	2.493(27.50)	2.500(27.28)
48000	2.507(27.06)	2.514(26.85)	2.522(26.63)	2.529(26.42)	2.536(26.21)
49000	2.543(26.00)	2.551(25.80)	2.558(25.59)	2.565(25.39)	2.573(25.19)
50000	2.580(24.99)	2.588(24.79)	2.595(24.59)	2.603(24.39)	2.610(24.20)
51000	2.618(24.01)	2.625(23.81)	2.633(23.62)	2.641(23.44)	2.649(23.25)
52000	2.656(23.06)	2.664(22.98)	2.672(22.70)	2.680(22.52)	2.688(22.34)
53000	2.696(22.16)	2.704(21.98)	2.712(21.81)	2.720(21.63)	2.728(21.46)
54000	2.736(21.29)	2.744(21.12)	2.753(20.95)	2.761(20.79)	2.769(20.62)

Figure 1.—Weight scaling tables for selected values of load weight and log number per load. Figures in parentheses are percent error associated with a 95% confidence interval for each estimated mean value of truckload board-foot volume. These are example tables only and not applicable to any current sale.

2). We then wrote a small computer program, using the regression equations, which computes and prints all desired combinations of values for a specific equation (in this case, Eq. 3 for all data). The table format is similar to other published tables (Tyre et al. 1973). Although two program steps are involved, the small increase in processing time is more than offset by flexibility in the choice of possible regression equations.

Potential Sources of Variation

Since our regression equations did not explain variability to the same degree as those in the South, we investigated possible sources of variation. The weight-to-scale ratio, or pounds per board-foot volume, is more sensitive than gross scale to variables measured in this study. Chief among these variables are sale origins of truckloads, season of the year in which loads are scaled, load mix of old-growth and blackjack pine logs, and load mix of log lengths. We used analysis-of-variance techniques to test whether differences in the weight-to-scale ratio could be attributed to any of these measured variables.

Sale locality integrates more fundamental sources of variation such as soil, climate, and local tree differences, which may vary widely over a large forest area. Our analysis showed significant estimation errors when regression equations from the Bly sale were used to scale volume from other sales (table 3). From a practical viewpoint, this means weight-scaling regressions based on one sale area should not be applied routinely to another sale area without verification. However, if a composite regression, covering more than one sale for a given species, could successfully estimate board-foot scale within prescribed precision limits for each sale in the group, the single regression equation may be more economical than using a separate equation for each sale. This possibility was tested and is discussed later.

Seasonal changes in moisture content can make a significant difference in log weight (Yerkes 1967, Markstrom and Hann 1972). To test seasonal differences, we computed regression equations derived from spring-season scaling data and applied them to truckloads scaled in summer and fall. Accuracy figures shown in table 3 are not conclusive. In this test, differences either did not exist or were cancelled out by compensating seasonal errors. Because our data only reflected time of year logs were measured, not when cut, a timing lag may have overshadowed any moisture differences due to season. Despite our lack of conclusive evidence on this point, caution must be exercised when using data taken in one season to estimate volume in another season.

The remaining two variables—blackjack-old growth mix and log-length mix—describe individual log loads. Gross scale and the weight-to-scale ratio for each load are affected by log type as indicated by the following correlation coefficients:[2]

	Gross scale Scribner Decimal C	Weight-to-scale ratio
Weight	0.536	Not applicable
Number of logs	-.407	0.648
Number of scaled pieces, 16 ft. or less	-.314	.622
Number of long logs	-.080	.400
Number of blackjack logs	-.226	.248
Number of old growth logs	-.254	.478
Proportion of long logs in the load	.411	-.268
Proportion of blackjack logs in the load	-.210	.200

Table 3.--Estimation precision of three regression equations[1] when applied to data from different timber sales and from different seasons[1]

Sale name or season	Truckloads compared	Regression equation number	Total scaling error		Mean truckload error
	No.		*M fbm*	*%*	*M fbm*
SALE:					
Fisher	22	1	33.747	28.8	1.534
		2	28.765	24.5	1.308
		3	29.027	24.7	1.319
Newman	104	1	94.264	17.1	.906
		2	45.227	8.2	.435
		3	45.233	8.2	.435
Pine Mountain	116	1	88.692	17.9	.765
		2	45.720	9.2	.394
		3	41.374	8.3	.357
Robber's Roost	29	1	12.419	8.1	.428
		2	2.550	1.7	.088
		3	2.476	1.6	.085
Whitehorse Burn	32	1	70.456	51.4	2.202
		2	21.701	15.8	.678
		3	16.407	12.0	.513
SEASON:					
Summer	82	1	44.591	11.9	.548
		2	4.930	1.3	.060
		3	11.890	3.2	.145
Fall	230	1	27.122	2.3	.118
		2	34.310	3.0	.154
		3	50.040	4.2	.218

[1]See table 2. Regression equations are based on Bly sale only and on spring season only.

[2]*For 531 truckloads including the six largest sales, a correlation coefficient for these variables is statistically significant at the 5% level if it is greater than 0.086. All log type variables except one are related to some degree with gross log scale and the weight-to-scale ratio, unless a 1 in 20 chance has occurred.*

An increasing number of logs per load for a given weight decreases board-foot scale because small logs scale less. In the gross-scale column, all correlation coefficients relating gross scale and the various log types are negative with one exception. For a given weight and number of logs, gross scale is positively correlated with the proportion of long logs on the truck. We did not have data to indicate which long logs were also old-growth logs, but there was a strong, positive correlation between number of long logs and number of old-growth logs per truckload. Old-growth logs increase gross scale because they tend to be those that most easily could be bucked as 32-foot or longer pieces and maintain an acceptable upper saw-log diameter limit. As expected, the proportion of blackjack logs is negatively correlated with gross scale.

Signs of correlation coefficients in the column for weight-to-scale ratio are all opposite from those for gross scale. When weight is fixed, any factor tending to decrease gross scale would, of necessity, increase the ratio of weight to scale.

Although correlations between all factors except gross scale and number of long logs are statistically significant, these factors improved predictive regression equations only slightly. Thus factors describing the type of logs in a load might be incorporated into regression equations only if they are already being measured for other reasons.

Relative Precision of Weight Scaling Methods

The three equations examined here are regression equation 3 (the most precise) discussed in an earlier section, and the regression equations for sample-stick scaling and ratio weight scaling. The last two equations are:

Sample-stick scaling,

$$\hat{v} = b_0 = \frac{1}{n} \sum_{j=1}^{n} v_j \qquad \text{[Eq. 4]}$$

Ratio-weight scaling,

$$\hat{v} = b_1 w = rw = \frac{\sum_{j=1}^{n} v_j}{\sum_{j=1}^{n} w_j} (w) = \frac{\bar{v}}{\bar{w}} (w) \qquad \text{[Eq. 5]}$$

where:

$\hat{v}$ = estimated truckload gross saw-log volume in thousand board feet,

n = number of sample truckloads (68 in this instance),

v_j = volume of each truckload in the sample ($j=1, 2 \ldots, 68$),

w_j = weight of each truckload in the sample ($j=1, 2 \ldots, 68$),

r = ratio of mean volume to mean weight of sample truckloads,

$\bar{v}$ = mean volume for sample truckloads,

$\bar{w}$ = mean weight for sample truckloads.

In order to test the relative precision of each equation, a sample of 68 truckloads was picked by methods described in the appendix. From analysis of this sample data, values were found for each regression coefficient in the three equations (table 4). Then, board-foot volumes for the 539 truckloads were estimated using each equation. Each of these regression equations has an associated variance and standard deviation which, combined with other terms, determines the precision of the estimate. Cochran (1963, p. 199-200) shows that under certain statistical conditions, a regression estimate can be more precise than a ratio or mean estimate. In weight-scaling terms, the regression of gross volume on truck weight and number of logs can be more precise than sample-stick or ratio weight scaling.

Known volumes from the 100-percent stick scale of all loads were compared with estimates from the three scaling methods to find which method best estimated total volume of all truckloads and the volumes for individual truckloads.

To compute estimated total volume for sample-stick scaling, the mean load volume for the 68 sample loads is multiplied by total number of loads (539); for ratio weight scaling, the scale-to-weight ratio for the sample is multiplied by total weight of all loads.

The regression estimate is the most precise in terms of a smaller standard deviation (table 4). Table 4 also shows total scaling error for each equation as the total difference between the 100 percent stick scale and predicted volume, and as percent error.

Estimating each truckload individually allows examination of the error patterns with respect to the estimating equation. The last two columns of table 4 show truckload error. The mean is the average difference for a truckload between actual and estimated volume. Of course, a given truckload might vary much more than these average figures. The regression equation estimated mean truckload volume especially well, although both weight and number of logs must be known to use it.

Consistency in estimating individual truckload volume is also important. Even if the average truckload error is close to zero, it is desirable that individual differences cluster as closely as possible around the average. Standard deviation of the mean error for truckloads serves as a measure for consistency. For example, the last column of table 4 shows that estimation errors from Eq. 3 had a

Table 4.--Summary of coefficients for three scaling equations (computed from 68 observations), and their accuracy for total volume and for individual truckloads

Equation number and type of scaling	Summary of coefficients[1]					Standard error of estimate	Total gross volume[2]				Truckload error	
	b_0	b_1	b_2	b_3	R^2		Estimate	Standard deviation	Scaling error		Mean	Standard deviation[3]
							M fbm	*M fbm*	*M fbm*	%	*M fbm*	*M fbm*
3 Regression weight scaling	2.74211	0.07761 (0.03026)	-0.01007 (0.07326)	-0.04987 (0.10062)	0.40	0.690	2711.558	42.238	-0.498	-0.018	-0.001	0.637
4 Sample stick scaling	5.05960				([4])	.099	2727.124	53.249	-16.064	-.593	-.030	.930
5 Ratio weight scaling		[5].10033			([4])	.002	2665.752	52.431	45.309	1.671	.084	.831

[1]For regression equation 3, standard errors appear in parentheses below their respective coefficients. Standard errors of the coefficients for equations 4 and 5 are the same as standard error of the estimate.
[2]The 539 loads used to test each model contained 2,711.060 M fbm total saw-log volume.
[3]This standard deviation is for the mean truckload error, and has no direct relation with the standard deviation of the estimate for total gross volume.
[4]This statistic was not computed for these specialized regression forms.
[5]For equation 5, b_1 is equivalent to r, the "ratio-of-means" estimator.

smaller standard deviation than the others, and clustered most closely about the mean error value.

The last way considered here for examining accuracy is to compute percentage of truckload estimates falling within given limits of precision:

Precision limit (*Bd ft*)	Truckloads estimated by— Regression weight scaling	Sample-stick scaling	Ratio weight scaling
	— — — —	(*Percent*)	— — — —
100	12.4	8.3	10.8
200	26.9	18.6	20.8
300	40.4	28.6	27.5
400	49.5	36.5	37.3
500	59.0	42.9	45.8
600	65.9	49.7	52.5
700	74.8	54.9	59.4
800	81.3	62.3	65.9
900	86.1	68.6	72.4
1000	90.0	71.8	77.6

The regression weight-scaling equation estimated 12.4 percent of the truckloads within 100 board feet, while the sample-stick scaling equation correctly estimated 8.3 percent of the truckloads within 100 board feet. The regression weight-scaling equation estimated 90 percent of the loads within 1000 board feet of their true value.

Using Regression Weight Scaling Equations for Estimation

From the practical point of view, we would like the most accurate estimates possible. The study shows that all equations estimated total sale volume within 4 percent error. However, Eq. 3 performed better when estimating individual truckload volume.

Regression weight scaling is an efficient means of estimating gross log scale, but some precautions must be observed to maintain precision. Regression equations should not be applied to a new situation unless results are carefully verified. Two examples of indiscriminate application illustrate erroneous results which might occur.

A section of table 2 describes regressions computed using data from one sale only (Bly). When these equations estimate gross scale for five other sales, the results are misleading, as illustrated in table 3. These sales are widely scattered in the Mogollon Rim and Flagstaff vicinity of Arizona. It is not surprising that equations based on one sale are useless in estimating total gross scale for another sale, because the range of data for the Bly sale differs from that for several of the other sales.

The other example considers whether one composite equation based on all data from a group of sales can adequately estimate gross board-foot volume for each sale individually. Figures in table 5 suggest this procedure is not adequate. Only the

Newman sale was estimated within 4 percent of true scale by all tested equations. Many estimates were in error by more than 4 percent, but the best estimates are still from Eq. 3, the regression with both truck weight and numbers of logs as input variables.

Interestingly, if all scaling errors in table 5 are added for a given equation, the total is well within acceptable precision limits. If all the data from these six sales (531 loads) could be considered as coming from just one sale, any of the three equations would perform well. The same conclusions apply to the seasonal data in table 5.

Table 5.--Estimation error in percent of known volume of three regression weight scale equations based on all data and applied to individual sales and seasons

Sale name or season	Truckloads[1]	Weight scale equation-- 1	2	3
	No.	*%*	*%*	*%*
SALE:				
Bly	228	8.607	3.902	3.335
Fisher	22	-7.416	-11.572	-12.002
Newman	104	-1.267	.516	1.651
Pine Mountain	116	-10.452	-7.165	-6.997
Robber's Roost	29	3.683	4.219	5.030
Whitehorse Burn	32	-28.776	-3.964	-4.966
Weighted average value	[2]531	.143	.091	.073
SEASON:				
Spring	218	.791	-.893	-.669
Summer	82	-11.149	-3.450	-3.399
Fall	239	2.692	1.860	1.739
Weighted average value	539	-.004	.004	.047

[1]Eight observations were omitted from sale data because they came from three sales and are not enough to provide reliable percentage results on a per-sale basis; these observations are included in the seasonal data. These data differences account for the slight discrepancies in total line percentages.
[2]This figure is the total number of truck loads considered.

Thus one sale cannot be satisfactorily weight scaled by using equations based on another sale; nor can individual sales in a group be weight scaled using a regression based on all sales in the group. One possible exception to these general rules occurs if both statistical analysis and common sense indicate that two or more sales are extremely similar with regard to cut-tree maturity, size, and harvest location. Even then caution is important.

Any reader considering application of these sample weight-scaling methods should read Tyre et al. (1973) and Wensel (1974) which give more detail on sampling and operational regression weight scaling.

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Appendix—Sample Size Determination

Let the 539 truckload observations for this study represent all loads from one hypothetical "sale." Assume we have an estimate of mean load volume and population variance obtained from cruise data, and that we expect about 550 loads from the sale.

Freese (1962) gives an equation for determining sample size when using simple random sampling. Since values for percent error and percent coefficient of variation are often known or estimated, modify Freese's equation to include percent error (PE) and percent coefficient of variation (CV) as follows:

$$n = \frac{1}{\left(\frac{PE}{CV}\right)^2\left(\frac{1}{t^2}\right) + \frac{1}{N}}$$

where:

n = number of truckloads in the sample,

N = estimated total number of loads,

$PE = \frac{E}{\bar{x}} \times 100\%$,

$CV = \frac{s}{\bar{x}} \times 100\%$,

$\bar{x}$ = estimated mean truckload board-foot scale in M fbm,

t = student's t value; for N larger than 25, $t \approx 2$,

E = one-half the width of the desired confidence interval, that is, the precision for the sample estimate of the mean, M fbm,

s = estimate of standard deviation of the population in M fbm.

The following steps with example calculations illustrate computation of sample size:

1. Estimate average load size in M fbm from cruise data or other sources.
   $\bar{x}$ = Average truckload volume = 5.00 M fbm.
2. Estimate truckload volume standard deviation from experience, cruise data, or presale sample.
   s = truckload std. dev. = 0.910 M fbm.
3. Compute estimated percent coefficient of variation by dividing s by $\bar{x}$.
   $$CV = \frac{s}{\bar{x}} \times 100\% = \frac{0.910 \text{ M fbm}}{5.000 \text{ M fbm}} \times 100\%;$$
   CV = 18%.
4. Decide on allowable percent error in sale estimate. Normally, this would be 2, 3, or 4%.
   PE = 4% error.
5. Estimate total number of log loads from estimated total sale cruise volume and from estimated average load size.
   $$N = \frac{\text{Estimated total cruise volume}}{\bar{x}} = \frac{2{,}750 \text{ M fbm}}{5.0 \text{ M fbm}} = 550 \text{ loads}$$
6. Since N is greater than 25, Student's t value is approximately 2.
7. Substitute all these quantities into the equation for sample size, n.

$$n = \frac{1}{\left(\frac{4}{18}\right)^2\left(\frac{1}{2^2}\right) + \frac{1}{550}} = 70.60$$

Using the next higher whole number, the desired sample size, n, is 71. Seventy-one numbers with possible values from 1 to 550 were picked from a random number table. The idea here is to take weight and volume data on those designated loads as they arrive. As it turned out, three of the random numbers picked were greater than 539 (the actual number of loads in the example sale) so only 68 truckloads were sampled. Missing three truckloads will not seriously jeopardize the sample. The sample data for the simulated sale is summarized here:

	Saw-log volume (*M fbm*)	**Weight** (*Pounds*)	**Logs** (*No.*)
Average load	5.060	50,428	16.8
Standard deviation	0.871	8,111	8.0
Range	7.310	79,770	69
	3.140	36,920	10

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Donnelly, Dennis M., and Roland L. Barger.
1977. Weight scaling for southwestern ponderosa pine. USDA For. Serv. Res. Pap. RM-181, 9 p. Rocky Mt. For. and Range Exp. Stn., Fort Collins, Colo. 80521.

Weight scaling is an increasingly important alternative to stick scaling as average saw log size decreases. Regression weight scaling was found to be more precise than sample stick scaling or ratio weight scaling for estimating sale and truckload log volumes, but all three methods were acceptably precise. The most precise regression equation included both net load weight and log count. Individual truckload volumes may be estimated as part of a woodyard inventory system from weight scaling tables generated from regression equations. Potential errors are discussed with examples, and techniques for avoiding these mistakes are suggested.

Keywords: Weight scaling (log), scaling (log), *Pinus ponderosa.*

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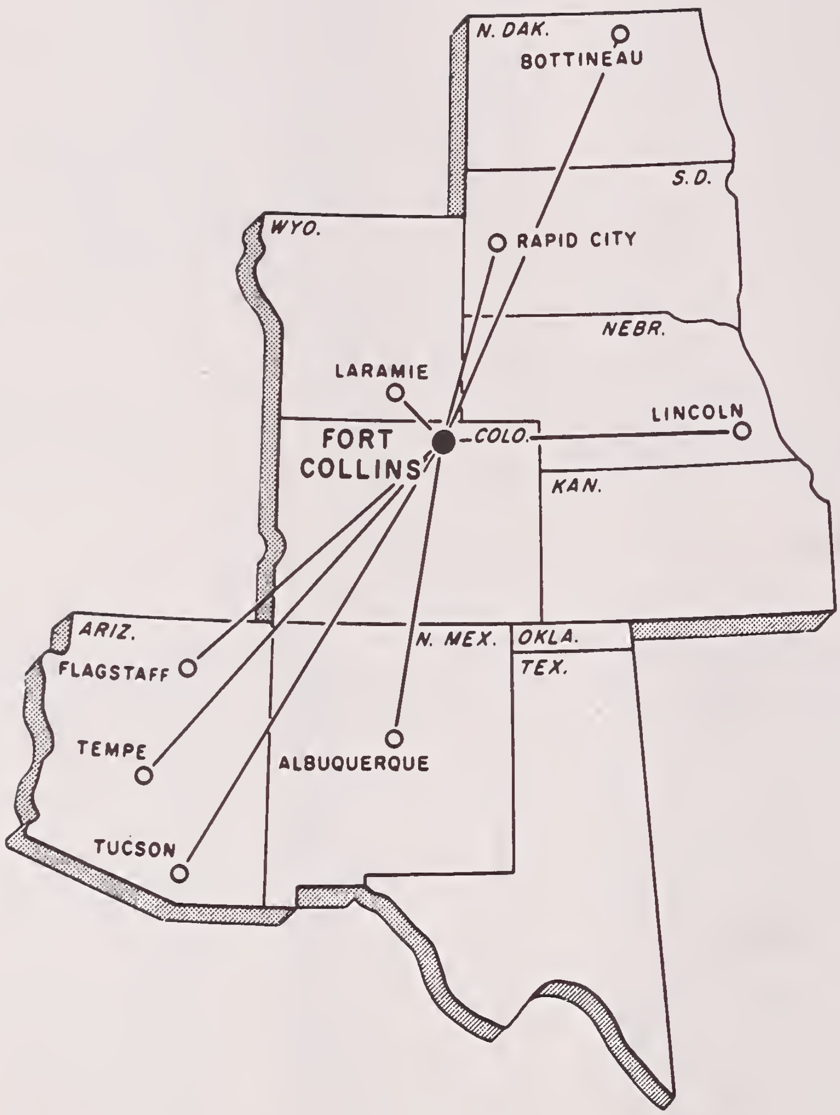
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